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Artificial-Intelligent-Enhanced Adaptive Vertical Beamforming Techniques for 5G Networks

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Abstract – The advances of 5G era systems and technology throughout the years suggests new uses for Adaptive beamforming and Digital Signal Processing (DSP) strategies in the communication systems to determine the transformational capacity of 5G wireless technology. This article evaluates the performance metrics of phase shift beamforming in a system of phased Uniform Rectangular Array (URA) aided with Artificial Intelligence (AI) to improve the link and communication quality in dense user urban environments. We use the conventional Quadrature Amplitude Modulation (QAM) for evaluating its robustness through a series of simulations for Bit Error Rate (BER) under different Signal to Noise Ratio (SNR) values. This study describes the opposition of theoretical and empirical BER to confirm the beamforming algorithm's operation in the communication system. We propose a spatial spectrum technique for a clear visualization of the Direction of Arrival (DoA) that gives the details of signal movement of users in the network and array behavior in the base station (BS). So, these results not only confirm the proposed methods effectiveness in the mobile network, but also highlight the importance of a creative AI system embedded with beamforming in achieving the expected performance metrics and reliability for future 5G communication networks and beyond.

Keywords: A.I., Beamforming, BER, Vertical, Throughput,5G.

1. Introduction

The 5G era would bring about what have never seen before opportunities and challenges in wireless communication. Adaptive beamforming is the pivot of this change; an essential technology that makes it possible to utilize the spectrum efficiently and at the same enhancing signal quality by directing the transmission power to where it is intended in real time [1]. At the heart of the transformation is Artificial Intelligence (AI), which helps to improve the beamforming methods and to maximize the effective employment of the spectrum while at the same time enhancing signal quality. Thus, in the present paper, we discuss this unique application based on adaptive vertical beamforming with AI involving designed to boost the efficiency and reliability of future 5G networks compared to its predecessors [2].

Sometimes the communication to the network requires that the user equipment (UE) is using some applications and at the same time be moving as pedestrian or by car, according to 5G system beamforming facility, the beam must follow the user's movement, which need user tracking according to his movement. This is done by channel quality indicator (CQI) in 4G-Long Term Evolution (LTE) or by proximity discovery using device-to-device D2D [3][4]. This points to the desperate need for creative beamforming methodologies that go above and beyond traditional techniques, specifically novel phase shift and spatial spectrum beamforming processes to help conquer the challenges of 5G mm-Wave frequencies and user congestion. On top of that, the brief survey demonstrates how an emerging use case of artificial neural networks has the potential to streamline the operation of beamforming, an essential aspect of enhancing the capabilities of 5G new radio systems [5].

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Through the complicated operations of Artificial Neural Networks (ANNs), this investigation opens a viable method for instantaneous adaptation and selection in beamforming where an immense improvement in accuracy and output is anticipated. Therefore, besides being an escape from various imperfections of traditional beamforming, it is also a gigantic move towards highly developed WCSs. However, beamforming is more than commendable for the present advancements in 5G owing to the fact that it is still anticipated to go as far as to permeate into the mmWave and terahertz bands of forthcoming networks [6].

This paper basically clears the lights on the emergence of smart beam-shaping techniques that will play a vital part in the introduction of 5G networks. It will focus on two techniques; phase shift and spatial spectrum beamforming to cater for dense user scenarios and to harmonize with current communication standards. Experimentation with AI-powered machine learning algorithms concerning beam tracking in the two bands discussed is a big response to the identified challenges concerning directional beamforming gain and the need for beam management frameworks to become more efficient.

We start by justifying the imperativeness of original beamforming solutions that aim to eliminate the challenges put forth by the conventional modulation approaches and the intricacies of the 5G mm-Wave frequencies. Our simulation framework provides a comprehensive assessment of such methods and their contribution to performance of the system where BER and throughput are under consideration depending on the case-related conditions.

This approach can illustrate the effectiveness of these methods in real life, and more importantly it can also prepare the ground for the future 5G research in beamforming that might explore the potential of the technology within their best operational environments.

The current study outlined several red flags that an efficient beam tracking system should pick up on, in addition to documenting the potential for integrating AI and machine learning systems to make wireless networks even faster and more effective.

We intend to link theoretical models with empirical data to give a detailed picture of what adaptive beamforming can do and how essential it is for the future of wireless communication networks. This research is very timely and necessary as the global movement towards 5G uptake increases the demand for wireless communication solutions that are strong, efficient and scalable.

The rest of this paper is as the following way; the previous works related to beamforming presented in section 2. Section 3 presents the mathematical model for adaptive beamforming with QAM scheme in 5G. Section 4 explains the proposed model and parameters assumptions and configuration. Section 5 presents the proposed system evaluation and results assessment. Finally, the paper presents the conclusions and future work in Section 6.

2. LITTERATURE REVIEW

The coming of 5G and the promise of 6G networks have resulted in a huge number of research initiatives that are aimed at improving network efficiency and data load. Significant advances have been made in the area of the adaptive beamforming, a key part of the large-scale Multiple Input Multiple Output (MIMO) infrastructure exploitation [7]. The article [8] provide a detailed study of the beamforming techniques and technologies that are at the core of the development of 5G networks. As high spatial concern is able to tackle the problem of the shortage of available space in the spectrum through using the millimeter wave, the following article comprehensively describes the approaches concerning analog and digital beamforming. The article also summarizes the studies investigating 5G communication improvement and speeds and remits encouraged by the International Telecommunication Union. The current study expresses how the combination of the current beamforming method with different antennas and substrates contributes to obtaining a higher data rate and increased coverage. It was a substantial number of limitations and advantages to every current technology mentioned in this article. However, it should be concluded that all of them are playing a crucial role in the deployment of 5G technologies in different industries.

In [9] the focus is then swayed towards the enhancement of the Random Access (RA) process in 5G networks; this is implemented within the novel concept of beamforming. By developing an Enhanced Random Access (E-RA) model, this study identifies high path-loss and narrow beam coverage as the fundamental challenges in 5G networks; hence new RA approach is needed. The novel E-RA process proposed in this study, by integrating beam-sweeping and beam-switching to cut access delay, lower energy consumption, and boost RA success probability. Therefore, this paper’s contribution is one of how beamforming could be used to improve network efficiency and user experience within the 5G cellular networks. Paper [10] has studied an adaptable mixed analog-digital beamforming technique for such networks and shown proof of the potential of the concept to aid 5G MIMO mmWave broadband networks in meeting dynamic traffic demands. Using vertical antenna arrays and ON-OFF antenna mode, this work has shown remarkable enhancement in the annual cumulative distribution function of the throughput, the blockage probability, downlink transmission power. The mixed digital-analog beamforming versatile nature considerably decreases the active radiating components, hence indicating a path towards hardware-efficient broadband wireless networks.

Monte Carlo simulation outcomes have affirmed that adaptive beamforming concept has high promise of significantly boosting network performance and hence contributes to the 5G technologies.

In [11] a prominent work of authors is a deep learning framework specifically created for adaptive beamforming in massive MIMO settings. This work demonstrates the capability of deep learning approaches in handling the complexities of millimeter-wave multicellular networks. At the same time, the outdoor mm-wave transmissions research, which is the subject of [12], introducing the adaptive analog beamforming as the base technology for spatial control of the millimeter-wave wireless signals has been developed. This technology is very crucial in resolving the in-built propagation problems caused by the high frequency 5G signals.

Another work in [13] focuses on the integration of MIMO systems with Non-Orthogonal Multiple Access (NOMA) which offers an in-depth investigation of beamforming techniques suitable for the specific requirements of 5G and subsequent network generations. To eliminate the difference between the theoretical models and the practical applications, the literature review in [14] showed where the artificial intelligence and beamforming and beam management intersect. In addition to the current development of beamforming techniques driven by AI this survey also provides some potential research opportunities and future directions that may enhance 5G network performance.

In [15], in our previous article, we concluded that A.I.'s decision-making process was exactly analyzed showing its capability to fine-tune beam direction in the presence of noise and interference. Also, the study concluded that A.I.-based steering towards the least power-intensive user is not only viable but also enhances overall network efficiency and reliability.

Finally, the development of the cellular technology with an emphasis on the role of hybrid beamforming in massive MIMO systems is analyzed in [16].

This research reviews the performance of hybrid beamforming in the development of high data rates, thereby, adding to the efficiency of the network in handling extremely huge amounts of data.

3. Mathematical System Model

QAM is crucial in adaptive beamforming, allowing for the efficient transmission of data by changing the amplitude of two carrier waves. These carrier waves, usually out of phase by 90 degrees (a sine and a cosine), are modulated by the digital data signal, allowing for a higher data rate within the same bandwidth:

- **Signal Model with QAM Modulation:**

The transmitted signal for an (M) −QAM system is:

$$[x_i(t) = I_i(t)\cos(2\pi f_c t) - Q_i(t)\sin(2\pi f_c t)] \qquad (1)$$

where $(I_i(t))$ *and* $(Q_i(t))$ represent the in-phase and quadrature components of the (i) -th user's signal, respectively. This representation is fundamental as it combines both components to efficiently utilize bandwidth and improve signal clarity in crowded network environments.

- **Antenna Array Reception and Beamforming:**

The received signal at each antenna element, including the effects of the channel and noise, is:

$$[x_n(t) = \sum_{i=1}^{4} a_n(\theta_i) \cdot x_i(t) + n_n(t)] \qquad (2)$$

and the beamformed output, which is a linear combination of received signals weighted by the beamforming vector (w), is given by:

$$[y(t) = w^H x(t)] \qquad (3)$$

where (w) is the weight vector optimized to focus the beam towards the desired user signal.

- **Adaptive Beamforming Algorithm**:

The beamforming vector is optimized through an algorithm that maximizes the SINR, crucial for maintaining signal quality in noisy environments:

$$[\max_w = \frac{w^H R_s w}{w^H R_n w}.] \qquad (4)$$

where R_s and R_n are the signal and noise covariance matrices, respectively. This optimization helps in dynamically adjusting the beam pattern to maximize reception quality.

- **QAM BER Estimation:**

The bit error rate (BER) for an (M)-QAM modulated signal can be estimated as:

$$[\mathrm{BER} \approx \frac{2\left(1 - 1/\sqrt{M}\right)}{\log_2(M)} Q\left(\sqrt{\frac{3\log_2(M)\cdot \mathrm{SINR}}{M-1}}\right)] \qquad (5)$$

This formula shows the error probability as a function of modulation order M and SINR, providing a quantifiable measure of the system's performance under varying conditions.

- **Throughput Calculation:**

The throughput of the system, defined as the rate at which data is successfully transmitted over the channel, is calculated as:

$$[\text{Throughput} = R_s \cdot (1 - \text{BER})] \tag{6}$$

where $(R_s)$is the symbol rate, and BER is the bit error rate. In the context of adaptive beamforming, (R_s) can be optimized based on the channel conditions and the beamforming algorithm's effectiveness. For an (M)-QAM system, the symbol rate relates to the bit rate $((R_b))$ as $(R_s = R_b/\log_2(M))$, hence the throughput in bits per second (bps) is:

$$[\text{Throughput} = R_b \cdot (1 - \text{BER}).] \tag{7}$$

Considering adaptive beamforming where the main lobe of the beam is directed towards the user with the least power, the SINR improvement directly influences the BER and, consequently, the system's throughput.

- **Noise Figure Added to Signals:**

The mathematical formula for generating a sample of this complex Gaussian noise can be expressed as:

$$[n = \sqrt{\frac{N_0}{2}} \cdot (n_R + jn_I)] \tag{8}$$

where:
- (n) is a sample of the generated complex Gaussian noise.
- (N_0) is the total noise power (which is referred to Noise Figure in this paper.).
- $(\frac{N_0}{2})$ ensures that the noise power is equally divided between the real $((n_R))$ and imaginary $((n_I))$ components of the noise. Both (n_R) and (n_I) are generated from a standard normal distribution (mean = 0, variance = 1).
- (j) represents the imaginary unit [17][18].

4. System Model And Parameters Assumptions

The system model, as shown in Figure 1, that was developed for the study is placed within a mobile network context where the central communication hub is a base station (BS), which interacts with a number of UEs within a defined coverage area. The BS that is equipped with complex signal processing systems is responsible for guiding the beam and maintaining a dependable link to the UE. In such a network, mobile users (referred to as User 1 and User 2) are mobile all the time and make the direction of arrival (DoA) of the signal dynamic; hence, the need for an adaptive signal processing. On the contrary User 3 and User 4 are static, being inside a building of different heights, where signal transmission meets multipath propagation effects caused by reflections, causing phase and time delays. The model shows the realities of signal propagation in the real world and the need for advanced beamforming methods to meet the complex communication needs within a 5G network environment. Machine learning, particularly deep learning, can be integrated into beamforming system models to dynamically adjust beam patterns based on real-time data. The system can learn from data and make adjustments to optimize beamforming strategies. This approach not only improves signal quality and system efficiency but also reduces latency and energy consumption by minimizing manual recalibrations and adjustments. The inclusion of ML algorithms transforms traditional beamforming into a more adaptive, efficient, and intelligent system capable of handling the complexities of modern 5G networks. This integration represents an enhancement in the system model, ensuring it remains robust in the face of varying network conditions and user demands.

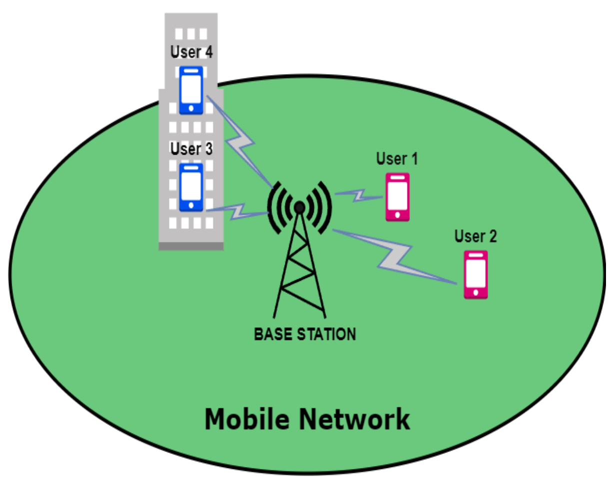

Fig. 1 Proposed System Model

Table I shows a summary for the important parameters and techniques used in the MATLAB simulation. It is also worth to mention that the main numerical parameters including frequency values, element layout, signal characteristics, noise level and the methods employed for signal processing, beamforming, and angle of arrival estimation in the context of a phased array system simulation are also included.

TABLE 1. Modeled System's Parameters Assumptions.

Parameter/Technique	Value/Description
Carrier Frequency	28GHz
Number of Elements in Array	8x8
Element Spacing	$(\lambda/2)$

Frequency Range	27GHz to 29GHz
Angle of Arrival (Horizontal)	Random integer between -90 and 90 degrees
Angle of Arrival (Vertical)	Random integer between 0 and 70 degrees
Noise Power	1.5 (1.76 dB)
Beamforming Direction	Based on the user with the lowest power signal
Phased Array Technique	Uniform Rectangular Array (URA)
DoA Estimation	MUlti SIgnal Estimator (MUSIC Estimator)
Modulation Order (M)	16 (QAM)
Symbol Rate	1 MHz
Frame Duration	1 ms
Eb/No Values	-25 to 25 dB
Number of Symbols Per Frame	100

The phased array technique utilized, specifically the Uniform Rectangular Array (URA), is optimized for high-density user environments characteristic of 5G networks. This array configuration is crucial for achieving precise angular resolution and superior signal integrity across the specified frequency range of 27GHz to 29GHz. The operational effectiveness of the URA is further enhanced by its ability to dynamically adjust the beam direction, accommodating the angular variability between -90 and 90 degrees horizontally, and 0 to 70 degrees vertically. These adjustments are critical in urban settings where line-of-sight pathways are frequently obstructed, necessitating agile and responsive beam steering capabilities to maintain robust communication links. Additionally, the choice of a 16-QAM modulation scheme supports the system's capability to handle higher data rates effectively, which is essential for supporting the increased throughput demands in 5G networks.

The flowchart in Appendix 1 outlines an AI-enhanced beamforming system designed for 5G networks, starting with the initialization of a URA, crucial for capturing and processing signals in a multi-user environment. Signals for multiple users are generated and then subjected to a unique set of scaling factors, optimizing their power levels for improved reception and processing efficiency. These signals undergo a beamforming process where the system dynamically selects the optimal direction based on the lowest power signal, demonstrating the adaptive nature of the system to focus on weaker signals and enhance overall network performance.

A feedback loop is incorporated to evaluate the system's performance continually, with BER and throughput calculations serving as key metrics. This loop allows for real-time adjustments to the beamforming strategy, ensuring the system's adaptability to varying network conditions and user requirements. Additionally, the system employs DoA and AoA estimation techniques, further refining the beamforming process by accurately determining the signal's origin. This precise localization is essential for targeting the beamforming efforts more effectively and is indicative of the system's capability to handle complex urban scenarios.

5. System Evaluation And Results Analysis

The actual signal representation for four different users is shown in Figure 2. The signals are generated and sampled over a 0.3s and a carrier frequency of 28 GHz, and thus represents signals used in millimeter-wave communications.

Each subplot depicts a single, brief high-amplitude pulse submerged in mostly 1V amplitude signal; these are digital pulses visualized in the time-domain. Each of the signal is further aligned with an element in a URA.

The signals are timed in such a way that each time at most one user signal is present; thus, the ultra-wide band spectra correspond directly to the spectrum for the four signals.

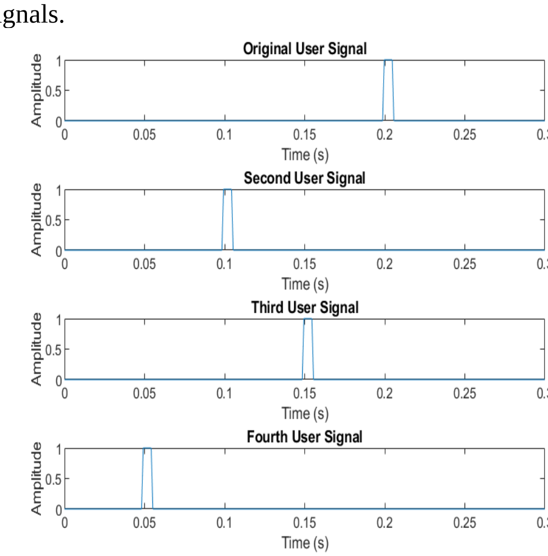

Fig. 2 Four Signals for End Users

Proceeding to Figure 3, which shows a three-dimensional spatial representation of user distribution with respect to a base station positioned at the center. The BS is defined at the coordinate origin to enable beamforming operations. The horizontal users (User 1 and User 2) exhibit the proximity of the base station in the XY plane and the vertical users (User 3 and User 4) are positioned along the Z axis reflecting a multi-story user environment that represents the urban high-rise conditions.

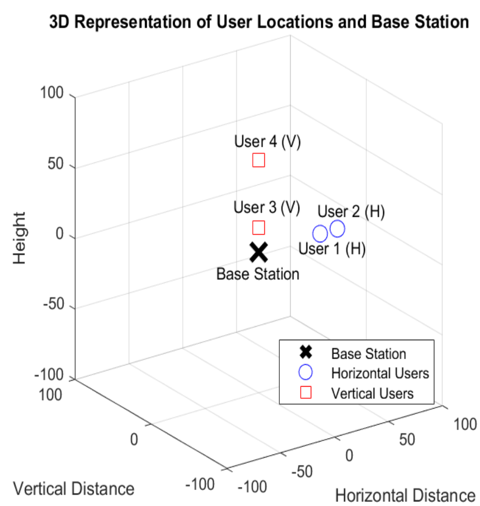

Fig. 3 3D Representation of Users Locations

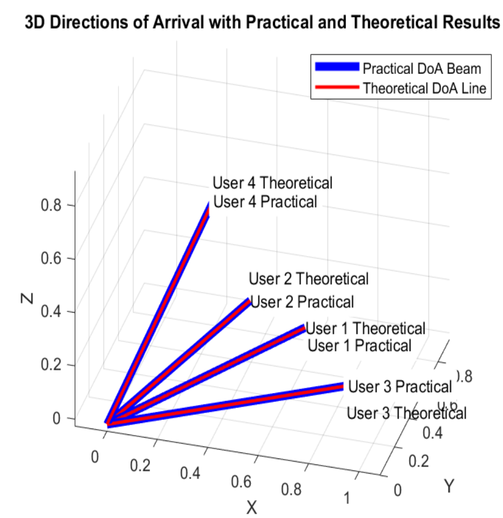

Fig. 5 3D representation of DOA

Figures 4, 5 and 6 present the spatial spectrum analysis utilized to infer the DOA for each user and their spectrum. Peaks are discernible for User 1 at approximately +57 azimuth degrees, User 2 at +73 azimuth degrees, User 3 at -8 azimuth and +9 elevation degree, and User 4 at -15 azimuth and +63 elevation degrees, with spectral magnitudes approaching unity. This precision in peak detection exemplifies the system's adeptness at resolving UE directions amidst a high noise backdrop, attributable to the MUSIC algorithm's high-resolution capabilities. DOA estimation in azimuth and elevation further validates the MUSIC estimator's proficiency.

Horizontal user's exhibit closely clustered azimuthal estimates, while vertical users are close at azimuth angles.

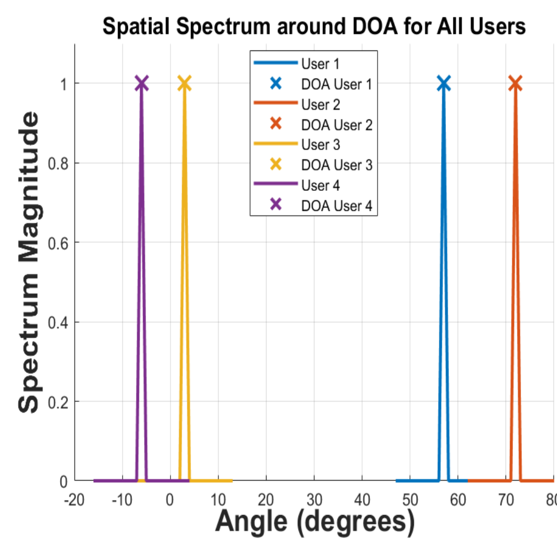

Fig. 6 Spatial Spectrum for all Users

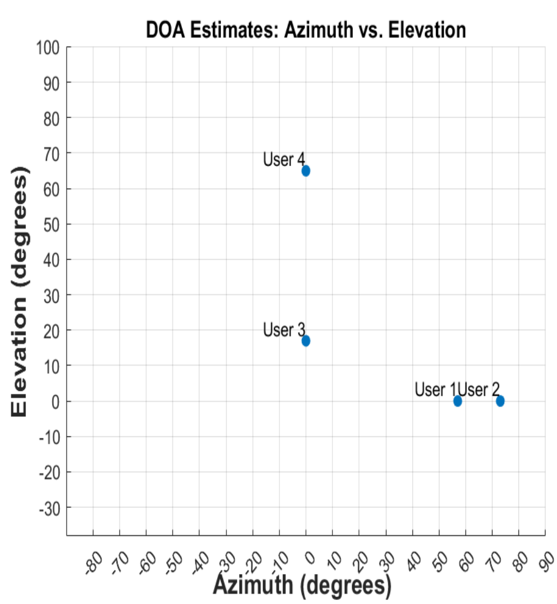

Fig. 4 DOA presentation in 2D

Figure 7, shows the original signal with heavy noise added to it to make it more challenging for the system to detect the signal. The right side shows that the signal is altered heavily beyond recognition as the noise figure added to the signal is 1.76 dB to imitate real environment scenario. The noise is added to every element in the array before transmitting the signal out.

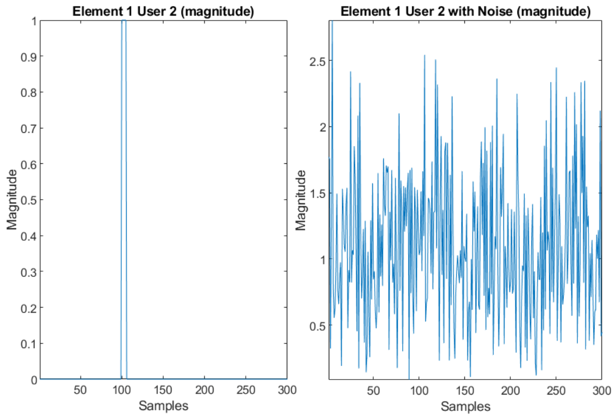

Fig. 7 Signal with Heavy Noise Addition

Figures (8 to 11), shows the response of azimuth and elevation arrays with and without beamforming weights implementation for Users 1 through 4. This focus is depicted by the narrowing of the main lobe and reduction of side lobes, translating to a more targeted signal at the intended user's location and less interference to others. These plots serve as a testament to the precision achievable with advanced beamforming techniques, emphasizing the potential to improve signal-to-noise ratios and overall system performance through careful design and weight optimization.

The normalized power in the beamforming application are significantly improved from an average level of -100 dB to a central peak at -20 dB, which is a strong 80 dB gain. This fact supports the effectiveness of the beamforming strategy in signal directivity improvement. Comparing the uniformity of the response without weights to the specificity with weights, these figures underscore the necessity of adaptive algorithms in 5G systems.

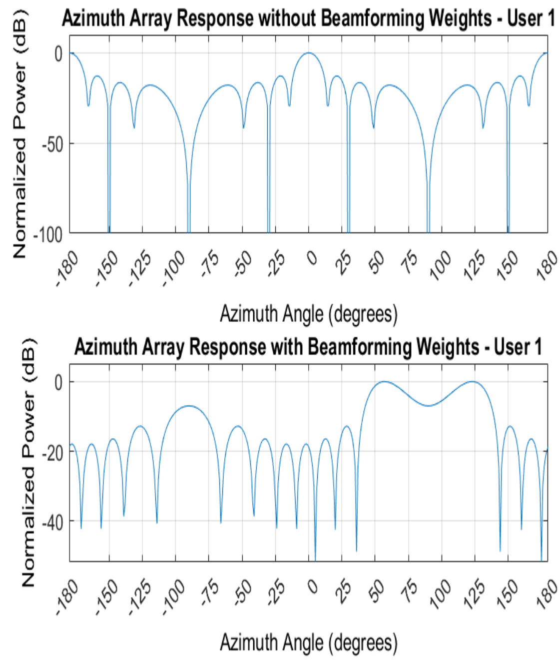

Fig. 8 Array Response for User1

Fig. 9 Array Response for User 2

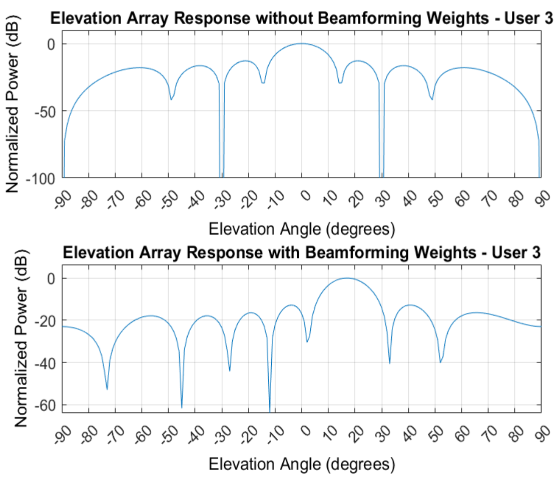

Fig. 10 Array Response for User3

Fig. 11 Array Response for User 4

Figure 12 demonstrates the impact of noise on the signal received by element 1 for User 2 in a 5G adaptive beamforming environment. The left graph displays a clean signal with a prominent peak indicating a strong received signal with minimal interference. It represents the temporal characteristic of the magnitude of the received signal after applying beamforming. The right graph introduces noise, simulating a more realistic operating condition. The signal's magnitude is visibly perturbed by the noise, resulting in a highly erratic and variable plot. This depicts the received signal strength varying significantly due to the influence of environmental noise and potential interference, a common challenge in 5G communications. Sporadic peaks ranging over 1.2 magnitudes break the plot and show that the system is a dynamic adaptation to the best beam alignment in the face of temporal changes in channel conditions. The comparison between the two states accentuates the significance of implementing effective noise-reduction strategies in beamforming algorithms to ensure signal integrity and system performance.

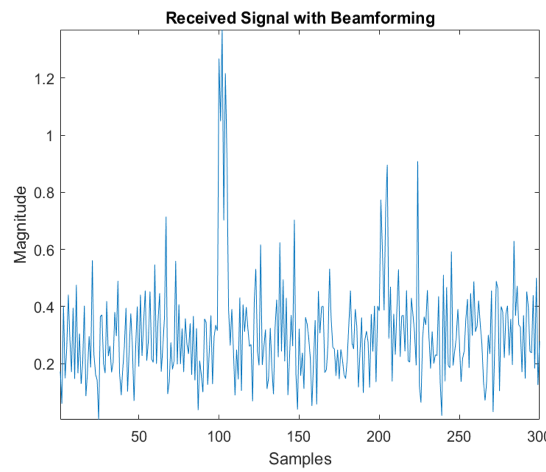

Fig. 12 Beamformed User's Signal

In Figure 13 the graph effectively illustrates the comparison between estimated and theoretical Bit Error Rate (BER) against the energy per bit to noise power spectral density ratio (Eb/No) for the user with the least power in a 5G network environment. It evaluates BER performance with respect to Eb/No which is a quantitative measure of data integrity. The blue stars indicate the estimated BER, derived from simulation results, demonstrating the practical performance of the beamforming system. The red dashed line plots the theoretical BER, calculated based on the mathematical models discussed in earlier sections of the paper. The convergence of estimated and theoretical values suggests that the simulation accurately reflects the anticipated performance, validating the system model. The BER estimates closely aligns with the theoretical BER with a clear exponential improvement seen as Eb/No grows. The BER falls under an acceptable 10^{-5} level at about 13 dB Eb/No which is suitable for reliable digital communications.

This underscores the effectiveness of adaptive beamforming in enhancing network throughput. It's observed that azimuth and elevation beamforming strategies improve throughput with increased Eb/No, demonstrating the techniques' ability to optimize data transmission in varied signal-to-noise conditions.

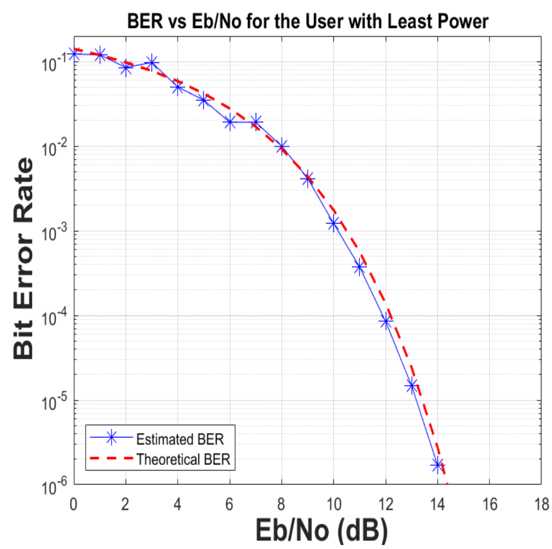

Fig. 13 Bit Error Rate Analysis

Finally, Figure 14 represents throughput comparison between azimuth and elevation beamforming with respect to the energy per bit to noise power spectral density ratio (Eb/No). It's observed that both strategies exhibit an increasing throughput with the rising Eb/No levels, eventually reaching a saturation point. The curve shows a vertical growth from 2.2 Mbps throughput at -25 dB Eb/No to a peak where it reaches its saturation at 3.8 Mbps, from 5 dB Eb/No. Notably, despite a higher noise figure in elevation beamforming, the use of a URA allows for spatial diversity utilization, enabling the elevation strategy to match the performance of azimuth beamforming at higher Eb/No values and outperforming the azimuth by 3.45% at lower Eb/No. Meanwhile, the azimuth approach, with its lower noise power, outperforms elevation beamforming by 6.25% at higher Eb/No; however, the gap closes as the Eb/No ratio improves, indicating effective compensation mechanisms within the system for noise.

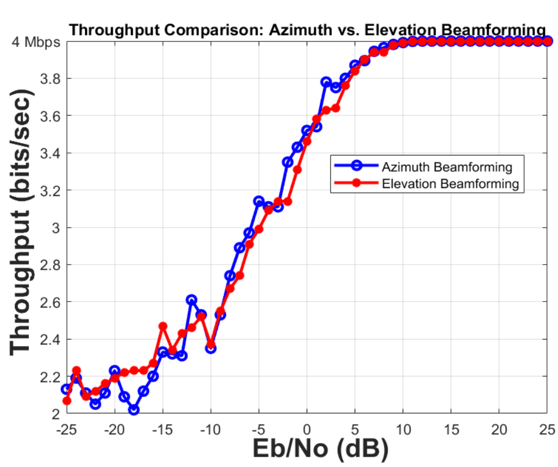

Fig. 14 Throughput Analysis

6. CONCLUSIONS

The complete system-level assessment of AI-enhanced beamforming methodology in crowded user environments with severe noise conditions as performed, validates the systematic approach. The system's behavior, as evidenced through complete throughput evaluations at high Eb/No ratios and correspondence to theoretical BER models, indicates that it operates as designed. Although DOA estimation is precise, it is evidenced that it can still be improved, especially in dealing with the speciousness introduced into the system via user mobility and channel variations due to time. Concerning the current beamforming system's complexity, there is still ample scope for future refinements. The full outcomes obtained from this examination validate sophisticated beamforming in advanced wireless communications, especially in urban terrains with complex user distribution. The study purports to make intelligent beamforming an essential part of the next-generation wireless network's base to allow such networks to manage the spatial transcript of broadcast communication proficiently under the incessantly changing conditions of urban communications. As future work, there are areas that provide a roadmap for continued research and development in the field of AI-enhanced adaptive vertical beamforming for 5G networks and beyond:

- Increasing the users is a difficult task as it requires increasing demands on managing the interference between them and raises higher concerns when facing environments with same or higher noise.
- Investigating the use of more sophisticated algorithms to improve DOA estimates for rapidly mobile users.
- Exploring how AI-enhanced beamforming techniques can be adapted for the 6G wireless communication networks, focusing on the integration of Terahertz (THz) frequency bands.
- Testing the beamforming algorithms with different antenna array configurations and hardware to assess real-world performance and limitations.

REFERENCES

[1] Al Janaby AO. 5G downlink throughput enhancement by beams consolidating at vacant traffic. Journal of Communications Software and Systems. 2019 Dec 3;15(4):311-6.

[2] Ngo, H., Fang, H., & Wang, H. (2020). Deep Learning-based Adaptive Beamforming for mmWave Wireless Body Area Network. *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, 1-6. https://doi.org/10.1109/GLOBECOM42002.2020.9322515.

[3] Al Janaby AO, Al-Omary A, Ameen SY, Al-Rizzo H. Tracking and controlling high-speed vehicles via cqi in lte-a systems. International Journal of Computing and Digital Systems. 2020 Nov 1;9(6):1109-19.

[4] Abdulqadir MQ, Al Janaby AO. Tracking Infected Covid-19 Persons and their Proximity Users Using D2D in 5G Networks. Journal of Communications Software and Systems. 2023 Mar 31;19(1):1-8.

[5] Upadhyay, D., Mittal, S., Jain, A., Sharma, R., Bagla, P., Tripathi, N., & Tiwari, P. (2023). An Artificial Intelligence Approach in 5G New Radio Beam Enhancement. *2023 Third International Conference on Secure Cyber Computing and Communication (ICSCCC)*, 641-646. https://doi.org/10.1109/ICSCCC58608.2023.10177035.

[6] (2023). Review of Artificial Intelligence Based Beam Tracking Techniques for mmWave 5G and Beyond Networks. *International Journal of Emerging Trends in Engineering Research*. https://doi.org/10.30534/ijeter/2023/081152023.

[7] Bhavana, K., Krishna, P., Nair, A., P, M., Menon, R., & Kiran, P. (2023). Efficient Beamforming Techniques in MU-MIMO. *2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN)*, 1521-1527. https://doi.org/10.1109/ICPCSN58827.2023.00253.

[8] Rao, L., Pant, M., Malviya, L., Parmar, A., & Charhate, S. (2020). 5G beamforming techniques for the coverage of intended directions in modern wireless communication: in-depth review. *International Journal of Microwave and Wireless Technologies*, 13, 1039 - 1062. https://doi.org/10.1017/s1759078720001622.

[9] Won, J., Kim, K., & Lee, T. (2021). Enhanced Random Access with Beamforming Techniques in 5G Networks. *2021 15th International Conference on Ubiquitous Information Management and Communication (IMCOM)*, 1-4. https://doi.org/10.1109/IMCOM51814.2021.9377362.

[10] Srinivas, K., Kiran, B., Sathvika, T., & Kishore, P. (2023). An Adaptive Hybrid Beamforming Technique for Analysis of Throughput, Blocking Probability, Transmission Power in 5G MIMO mmWave. *2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS)*, 1-6. https://doi.org/10.1109/ICSCSS57650.2023.10169422.

[11] S. Lavdas, P. K. Gkonis, E. Tsaknaki, L. Sarakis, P. Trakadas, and K. Papadopoulos, "A Deep Learning Framework for Adaptive Beamforming in Massive MIMO Millimeter Wave 5G Multicellular Networks," MDPI AG, Jul. 2023. Accessed: Mar. 06, 2024. [Online]. Available: http://dx.doi.org/10.20944/preprints202307.1926.v1

[12] J. Pérez Santacruz *et al.*, "Outdoor mm-wave 5G/6G transmission with adaptive analog beamforming and IFoF fronthaul," *Scientific Reports*, vol. 13, no. 1, Aug. 2023, doi: 10.1038/s41598-023-40112-w.

[13] S. U. Rehman, J. Ahmad, A. Manzar, and M. Moinuddin, "Beamforming Techniques for MIMO-NOMA for 5G and Beyond 5G: Research Gaps and Future Directions," *Circuits, Systems, and Signal Processing*, vol. 43, no. 3, pp. 1518–1548, Nov. 2023, doi: 10.1007/s00034-023-02517-w.

[14] D. da S. Brilhante *et al.*, "A Literature Survey on AI-Aided Beamforming and Beam Management for 5G and 6G Systems," MDPI AG, Mar. 2023. Accessed: Mar. 06, 2024. [Online]. Available: http://dx.doi.org/10.20944/preprints202303.0282.v1

[15] Othman Al Janaby A, Maher Al-Hatim Y. Artificial-Intelligence-Enhanced Beamforming for Power-Efficient User Targeting in 5G Networks. International Journal of Computing and Digital Systems. 2024 Feb 24;16(1):1-0.

[16] S. Hamid *et al.*, "Hybrid Beamforming in Massive MIMO for Next-Generation Communication Technology," *Sensors*, vol. 23, no. 16, p. 7294, Aug. 2023, doi: 10.3390/s23167294.

[17] J. G. Proakis: "Digital Communications", McGraw-Hill Education, 4th ed., 2013.

[18] C. A. Balanis: "Antenna Theory: Analysis and Design", Wiley, 4th ed.,2017.

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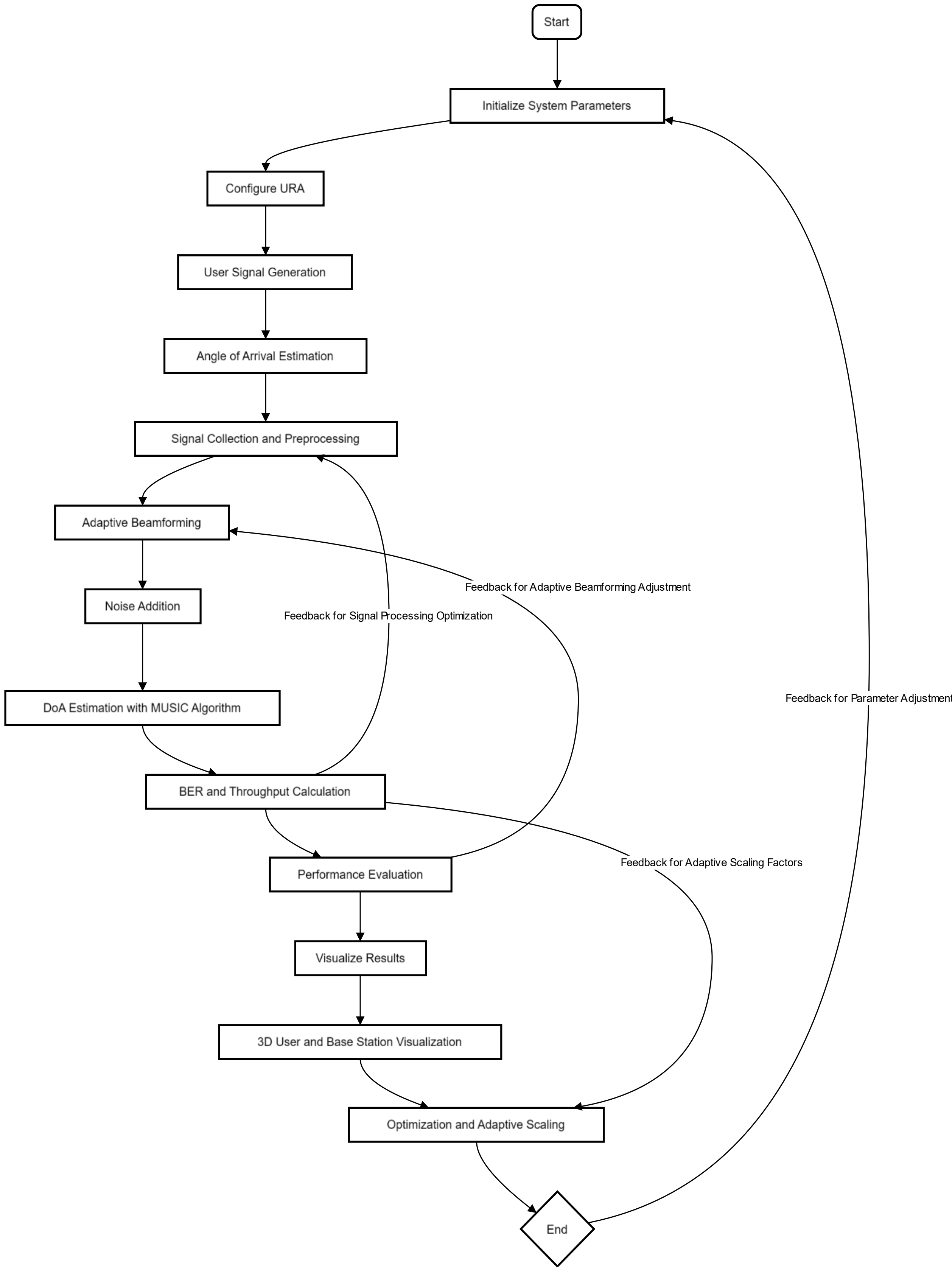
APPENDIX

Appendix 1: System's Flowchart


Start
Initialize System Parameters
Configure URA
User Signal Generation
Angle of Arrival Estimation
Signal Collection and Preprocessing
Adaptive Beamforming
Noise Addition
DoA Estimation with MUSIC Algorithm
BER and Throughput Calculation
Performance Evaluation
Visualize Results
3D User and Base Station Visualization
Optimization and Adaptive Scaling
End
Feedback for Adaptive Beamforming Adjustment
Feedback for Signal Processing Optimization
Feedback for Parameter Adjustment
Feedback for Adaptive Scaling Factors